

Monitoring Markov Chains

Mahyar Karimi

Institute of Science and Technology Austria

September 13, 2023



Coins

- ▶ Given two (*maybe fair*) coins:



- ▶ How different are the coins?

Coins

- ▶ Given two (*maybe fair*) coins:

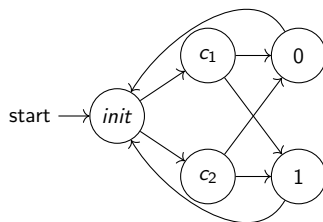


- ▶ How different are the coins?

$$\mathbb{P}(1 \mid c_1) - \mathbb{P}(1 \mid c_2)$$

Coins in Markov Chains

- ▶ Let's turn this into a Markov chain:

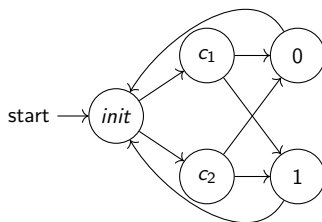


- ▶ Observing this Markov chain → Stream of states:

init, c₁, 1, init, c₂, 0, init, c₁, 0, ...

Coins in Markov Chains

- ▶ Let's turn this into a Markov chain:



- ▶ Observing this Markov chain \rightarrow Stream of states:

init, c₁, 1, init, c₂, 0, init, c₁, 0, ...

- ▶ How to estimate $\mathbb{P}(1 | c_1) - \mathbb{P}(1 | c_2)$?

What We Developed

- ▶ Techniques for estimating expressions over $\mathbb{P}(\cdot | \cdot)$
 - Frequentist and Bayesian: two well-known paradigms in statistics



What We Developed

- ▶ Techniques for estimating expressions over $\mathbb{P}(\cdot | \cdot)$
 - Frequentist and Bayesian: two well-known paradigms in statistics
- ▶ \implies Monitors for transitions in Markov chains

What We Developed

- ▶ Techniques for estimating expressions over $\mathbb{P}(\cdot | \cdot)$
 - Frequentist and Bayesian: two well-known paradigms in statistics
- ▶ \implies Monitors for transitions in Markov chains
- ▶ \implies Monitoring fairness properties!



The Frequentist, The Bayesian

- ▶ The *frequentist*
 - Probabilities \equiv Long-run frequencies
 - Estimating the *ground truth*.

The Frequentist, The Bayesian

▶ The *frequentist*

- Probabilities \equiv Long-run frequencies
- Estimating the *ground truth*.

▶ The *Bayesian*

- Markov chains sampled from a given distribution (*prior belief*).
- **No ground truth!** Only prior belief.

Frequentist Monitor

- ▶ Monitor: Input stream \rightarrow Interval stream:

$$\mathcal{A} : \Sigma^* \rightarrow I_{-\infty, \infty}$$

¹Probably **A**pproximately **C**orrect

Frequentist Monitor

- ▶ Monitor: Input stream \rightarrow Interval stream:

$$\mathcal{A} : \Sigma^* \rightarrow I_{-\infty, \infty}$$

- ▶ The monitor gives PAC¹-style guarantees (for given δ):

$$\mathbb{P}(\varphi \in \mathcal{A}(\vec{X})) \geq 1 - \delta$$

¹Probably **A**pproximately **C**orrect

Frequentist Monitor

- ▶ Monitor: Input stream \rightarrow Interval stream:

$$\mathcal{A} : \Sigma^* \rightarrow I_{-\infty, \infty}$$

- ▶ The monitor gives PAC¹-style guarantees (for given δ):

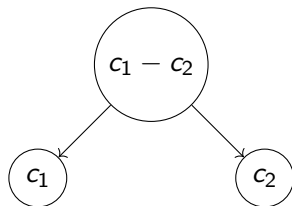
$$\mathbb{P}(\varphi \in \mathcal{A}(\vec{X})) \geq 1 - \delta$$

- ▶ Intervals \Leftarrow Bounding with Hoeffding's inequality.

¹Probably **A**pproximately **C**orrect

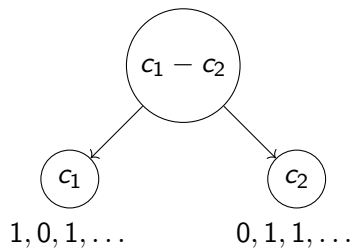
Frequentist and Coins

- For $\mathbb{P}(1 | c_1) - \mathbb{P}(1 | c_2)$:



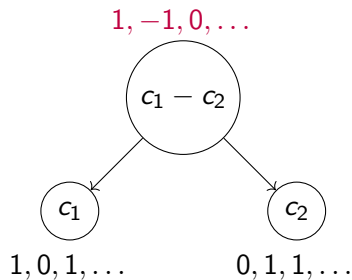
Frequentist and Coins

- For $\mathbb{P}(1 \mid c_1) - \mathbb{P}(1 \mid c_2)$:



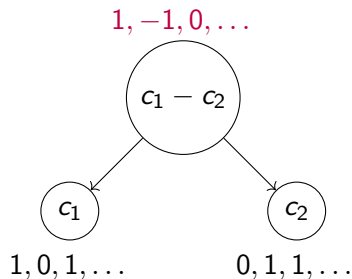
Frequentist and Coins

- For $\mathbb{P}(1 \mid c_1) - \mathbb{P}(1 \mid c_2)$:



Frequentist and Coins

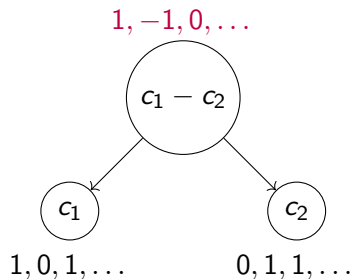
- ▶ For $\mathbb{P}(1 | c_1) - \mathbb{P}(1 | c_2)$:



- ▶ New RV with the **same expected value** as the subtraction

Frequentist and Coins

- ▶ For $\mathbb{P}(1 | c_1) - \mathbb{P}(1 | c_2)$:



- ▶ New RV with the **same expected value** as the subtraction
- ▶ A few other techniques for multiplication and division

The Bayesian

- ▶ Fixed *prior distribution*² θ over Markov chains (*prior belief*)
- ▶ Obtaining *posterior belief* after observing \vec{x}

²Matrix beta distribution

Bayesian Monitor

- ▶ The monitor guarantees the following (for given δ, θ):

$$\forall \vec{x} \in \Sigma^*. \mathbb{P}_\theta \left(\varphi(\mathcal{M}) \in \mathcal{A}_\theta(\vec{x}) \right) \geq 1 - \delta$$

Bayesian Monitor

- ▶ The monitor guarantees the following (for given δ, θ):

$$\forall \vec{x} \in \Sigma^*. \mathbb{P}_\theta \left(\varphi(\mathcal{M}) \in \mathcal{A}_\theta(\vec{x}) \right) \geq 1 - \delta$$

- ▶ Core component: efficient, incremental computation of $\mathbb{E}_\theta(\varphi(\mathcal{M}) \mid \vec{x})$:

$$\mathbb{E}_\theta(\varphi(\mathcal{M}) \mid \vec{x}ab) = \mathbb{E}_\theta(\varphi(\mathcal{M}) \mid \vec{x}a) \cdot \frac{c_{ab}(\vec{x}) + d_{ab}}{c_{ab}(\vec{x})} \cdot \frac{c_a(\vec{x})}{c_a(\vec{x}) + d_a}$$

Base case comes from θ .

Bayesian Monitor

- ▶ The monitor guarantees the following (for given δ, θ):

$$\forall \vec{x} \in \Sigma^*. \mathbb{P}_\theta \left(\varphi(\mathcal{M}) \in \mathcal{A}_\theta(\vec{x}) \right) \geq 1 - \delta$$

- ▶ Core component: efficient, incremental computation of $\mathbb{E}_\theta(\varphi(\mathcal{M}) \mid \vec{x})$:

$$\mathbb{E}_\theta(\varphi(\mathcal{M}) \mid \vec{x}ab) = \mathbb{E}_\theta(\varphi(\mathcal{M}) \mid \vec{x}a) \cdot \frac{c_{ab}(\vec{x}) + d_{ab}}{c_{ab}(\vec{x})} \cdot \frac{c_a(\vec{x})}{c_a(\vec{x}) + d_a}$$

Base case comes from θ .

- ▶ Intervals \Leftarrow Bounding with Chebyshev's inequality.



Monitoring Regular Expressions?

- ▶ So far: $\mathbb{P}(b \mid a)$

Monitoring Regular Expressions?

- ▶ So far: $\mathbb{P}(b \mid a)$
- ▶ $\mathbb{P}(b_1 \dots b_k \mid a)$ is not that different:

$$\mathbb{P}(b_1 \dots b_k \mid a) = \mathbb{P}(b_1 \mid a) \cdots \mathbb{P}(b_k \mid b_{k-1})$$

- ▶ \rightarrow^* Monitoring *star-free* regular expression r : $\mathbb{P}(r \mid a)$.